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Hybrid Ventilation System and Soft-Sensors for Maintaining Indoor Air Quality and Thermal Comfort in Buildings

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Abstract: Maintaining both indoor air quality (IAQ) and thermal comfort in buildings along with optimized energy consumption is a challenging problem. This investigation presents a novel design for hybrid ventilation system enabled by predictive control and soft-sensors to achieve both IAQ and thermal comfort by combining predictive control with demand controlled ventilation (DCV). First, we show that the problem of maintaining IAQ, thermal comfort and optimal energy is a multi-objective optimization problem with competing objectives, and a predictive control approach is required to smartly control the system. This leads to many implementation challenges which are addressed by designing a hybrid ventilation scheme supported by predictive control and soft-sensors. The main idea of the hybrid ventilation system is to achieve thermal comfort by varying the ON/OFF times of the air conditioners to maintain the temperature within user-defined bands using a predictive control and IAQ is maintained using Healthbox 3.0, a DCV device. Furthermore, this study also designs soft-sensors by combining the Internet of Things (IoT)-based sensors with deep-learning tools. The hardware realization of the control and IoT prototype is also discussed. The proposed novel hybrid ventilation system and the soft-sensors are demonstrated in a real research laboratory, i.e., Center for Research in Automatic Control Engineering (C-RACE) located at Kalasalingam University, India. Our results show the perceived benefits of hybrid ventilation, predictive control, and soft-sensors.

Keywords: indoor air quality (IAQ); hybrid ventilation; demand controlled ventilation (DCV); internet of things (IoT); soft-sensor; convolution neural networks

1. Introduction

The building sector in India currently contributes to ~37% of the total energy consumption of the nation and predicted to further increase by 8% annually due to recently proposed construction of 40 billion m^2 by 2050 which are driven by rapidly growing population and urbanization [1]. Statistics suggest that space cooling alone contributes to about 40–45% of the total building energy consumption in India. Consequently, energy optimization for space cooling maintaining thermal comfort has attracted significant attention recently (see [2,3] and references therein). While the importance of energy consumption is often exacerbated, the indoor air quality (IAQ) is not usually discussed [4]. However, IAQ is an important parameter that determines the productivity and performance of occupants in the building. The IAQ refers to the air quality within and around buildings and structures, especially it relates to the health and comfort of building occupants (https://www.epa.gov/indoor-air-quality-iaq/introduction-indoor-air-quality). The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) defines IAQ as Air in which there are no known contaminants at harmful concentrations as determined by cognizant authorities and with which a substantial majority (80% or more) of the people exposed do not express dissatisfaction (http://cms.ashrae.biz/iaqguide/pdf/IAQGuide.pdf?bcsi_scan_C17DAEAF2505A29E=0&bcsi_scan_filename=IAQGuide.pdf).

It is widely perceived that understanding the common pollutants and controlling them could reduce health concerns, which can either be short- or long-term. Common short-term effects include dizziness, headaches, and fatigue, whereas long-term effects could be respiratory diseases, heart diseases, and even cancer. There are many surveys which have shown that both IAQ and thermal comfort are not well maintained by current ventilation systems (see, for example, in [5–8]). This is mainly because IAQ, thermal comfort, and energy consumption are competing objectives. As an increase in IAQ means more fresh air induction which will increase the energy consumption and can lower down thermal comfort as well. Therefore, maintaining IAQ, thermal comfort and minimizing energy is a major challenge in buildings, but important for achieving energy goals as well as occupant performance in buildings.

There are two procedures commonly used for maintaining IAQ: (i) Ventilation Rate Procedure and (ii) Indoor Air Quality Procedure [9]. The later aims to strike a good balance between energy savings and IAQ. Furthermore, it provides direct reduction of indoor contaminants. Similarly, in practice, there are three approaches to improve IAQ: (i) source control, (ii) improved ventilation, and (iii) air-cleaners. In source control, we eliminate individual sources of pollution or reduce their emissions and is considered an effective method for maintaining IAQ. Ventilation improvements means forcing fresh air into the buildings by opening windows and doors when weather permits, but this may lead to energy loos. Air cleaners aim to remove the particle from indoor air and uses filtering blocks to remove pollutants. Among these methods, forcing fresh air is by far the cheapest method for maintaining IAQ. However, optimal fresh air should be infused to reduce energy consumption.

Over the years, several control approaches for maintaining both IAQ and thermal comfort have been studied but with certain limitations. Among those, few studies implemented model predictive control (MPC) to investigate the combined (i) thermal comfort and CO_2 optimization by regulating fresh air [10], (ii) IAQ (particle concentration) and energy optimization [11], (iii) multi-objective optimization of IAQ (particulate matter) and energy consumption in subway ventilation system [12], (iv) optimization energy and IAQ with focus on CO_2 [13], and (v) energy optimization and air-quality through fresh air induction [3]. More recently, the role of demand controlled ventilation(DCV) on IAQ and energy savings was studied [14]. Another study implemented MPC for energy optimization and monitoring carbon dioxide in commercial HVAC systems with an Internet of Things (IoT) based control [15]. A combined control for IAQ, energy and thermal comfort was proposed in [16] for variable air volume (VAV) controlled systems. Similarly, thermal comfort and IAQ in chilean schools with surveys was studied in [17]. The control of IAQ in direct expansion air-conditioning system was studied in [18]. However, most of these investigations have concentrated only on temperature, humidity, and carbon dioxide levels while discussing IAQ.

As for sensors, a WiFi-enabled IAQ monitoring and control system for buildings was proposed in [19]. A soft-sensor for measuring carbon dioxide content in the building by fusing carbon dioxide and PIR sensor was proposed in [20]. A soft-sensor for estimating cooling load using long short-term memory (LSTM) was proposed in [21]. A review of sensors for measuring Indoor Air Quality (IAQ) was presented in [22]. There are many studies on sensor design for IAQ or studying sensor installation/monitoring issues reviewing which are out of the scope of the paper. More recently, the use of soft-sensors for IAQ modeling was studied in [23] wherein sensor readings was used to train deep subspace network to model IAQ parameters. A soft-sensor for detecting urban IAQ was proposed in [24] using Bayesian networks. These results illustrated that by combining compact sensors with databased techniques capabilities of sensor could be overarched and they can be made more smarter. Albeit, such significant advantages, the role of soft-sensor has not been studied extensively.

A review of the literature reveals three gaps in control and monitoring in buildings. First, maintaining IAQ, thermal comfort and optimizing energy simultaneously is a challenge that has not been fully addressed in the literature. In particular, the ones concerning IAQ parameters such as Volatile Organic Compounds, Carbon-dioxide and others have not been combined with energy optimization based control and thermal comfort. Second, although low-cost sensors are available their reliability and performance is limited. To overcome this, soft-sensors which combine compact sensors with data analytics methods are gaining popularity. The advantage of soft-sensors is that they can also predict the variables and can also model variables which are not measured, e.g., cooling load. In addition, they provide smartness to the control. Third, the use of soft-sensors within control has not been reported. Our main objective is to address these research gaps in the literature by proposing a soft-sensor based ventilation method that could optimize energy consumption while maintaining IAQ and thermal comfort. The main contributions can be summarized as below.

1. Novel design of a hybrid ventilation system design which simultaneously optimizes energy consumption, maintains IAQ and meets thermal comfort as well.
2. Present the Internet of Things (IoT) architecture and sensor prototype for implementing the hybrid ventilation system.
3. Design soft-sensors for modeling and predicting IAQ parameters and cooling load.
4. Controller design for hybrid ventilation scheme that could use the soft-sensors and the IoT devices to implement a flexible control architecture.

The paper is organized into five sections. Section 2 presents the problem formulation and challenges. The hybrid ventilation system, soft-sensor design, and control techniques are presented in Section 3. Deployment results of the different components are presented in Section 4. Conclusions and future directions of the investigation are discussed in Section 5.

2. Problem Formulation

The objective is to design a novel hybrid ventilation system to maintain IAQ, thermal comfort in terms of set-point temperature and minimize energy consumption at the Center for Research in Automatic Control Engineering (C-RACE) at the International Research Center (IRC), Kalasalingam University, India. The lab houses faculty offices, startups in the building automation laboratory, research labs, researchers and visitors as shown in Figure 1. The current system consists of fans and variable refrigerant volume (VRV)-based air-conditioning system (package units) providing space cooling controlled by a thermostat which turns ON or OFF depending upon the user defined temperature limits. The lab has air quality issues due to the use of chemicals for making printed circuit boards in the startups, presence of human beings, particulate matter suspended due to tests conducted in electric vehicles laboratory and other contamination. Furthermore, some parts of the lab does not have air-conditioners rather fans for circulating air. There are exhaust fans for pushing the indoor air outside, but fresh air induction is currently only by opening doors.

The VRV systems are located in the electric vehicle lab (EV lab), building automation lab, research center on artificial pancreas, and software development lab. There is also the IAQ lab from where the hybrid ventilation system is to be implemented for maintaining IAQ, thermal comfort and energy optimization. Additionally, we plan not to make modifications to existing systems for example, the VRV system control or installing fresh air dampers in the space to avoid costly retrofits. In our analysis, the IAQ is modeled as

$$J_{IAQ} = f(PM, CO_2, TVOC, H, T) \quad (1)$$

where $PM, CO_2, TVOC, H$, and T denote the particulate matter, carbon dioxide(measured in ppm), total volatile organic compounds (measured in ppb), humidity, and temperature, respectively. These factors are time-varying and their dynamic is complex to model. The control variable that can influence the IAQ is the fresh air induction rate into the rooms u_{FA}, the fraction of total mass flow rate of fresh air that can be supplied to the room m_{FA}, and is given by

$$u_{FA} = (1 - d) \times m_{FA} \tag{2}$$

where $(1 - d)m_{FA}$ denotes the fresh air fraction that is supplied to the room. Similarly, to control the temperature and thermal comfort, we aim to change the control from being a simple thermostat to have additional degrees of freedom. This is required as there is no coarse control on the space possible with thermostat. To this extent, we could modify the time for which the air-conditioner is turned ON or OFF to modulate the average cooling power being supplied and this provides finer control over the temperature with pulse-width modulation sort of control. To this extent, we modify the control variable from being set-temperature to ON/OFF time. Assuming that the period for which the energy optimization is T_p which depends on the time constant of the room, then the control variable u_{AC} models the time for which the AC is turned ON and is given by

$$u_{AC} = \frac{t_{ON}}{T_p} \tag{3}$$

where t_{ON} is the time-period for which the AC stays ON. However, a turn-off AC could cause the air circulation to go down, thereby making occupants to feel thermal discomfort. This could be avoided by turning ON fans during such times. This procedure of turning on AC and fans, we term it as toggling. The energy optimization problem then could be implemented as a toggling action between the AC and fan. The duty ratio for the fan is

$$u_{Fan} = \frac{T_p - t_{ON}}{T_p} \tag{4}$$

We used eight fans in our work. Their heat generation was not considered in our study as they were very minimal compared to the room size and cooling load.

The energy consumption in AC and fan is given by

$$J_{Power} = u_{AC} \times P_{AC} + u_{Fan} \times P_{Fan} \tag{5}$$

where P_{AC} and P_{Fan} are the power ratings of the fan and air-conditioner, respectively. The thermal comfort of the occupant is modeled using the temperature bounds on the room which is given by

$$T_{min} \leq T(k) \leq T_{max} \tag{6}$$

where $T(k)$ is the temperature at time-instant k and T_{min}, T_{max} denote, respectively, the minimum and maximum temperature supplied by the occupant based on their thermal comfort. Determining that the temperature is within the user defined comfort band requires model of the zone corresponding to the ON/OFF times of the air-conditioner and fan. However, fan does not vary the room temperature, but only the skin temperature of the occupant. Therefore, the zone temperature depends on the current room temperature $T(k)$, ambient temperature $w(k)$ and stray heating due to occupancy, lighting loads and others modeled as a disturbance term $v(k)$. Following [2], we model the room temperature dynamics to be

$$T(k+1) = aT(k) - bu_{AC}(k) + cw(k) + v(k) \tag{7}$$

where a, b, c denote the thermal time constant of the room, the parameter that models the influence of air-conditioner cooling energy, and effect of weather on the room temperature, respectively. Similarly, there exists a minimum and maximum time for which the air-conditioner can be turned ON/OFF. This is modeled as

$$u_{AC_{\min}} \leq u_{AC}(k) \leq u_{AC_{\max}} \tag{8}$$

where $u_{AC_{\min}}$ and $u_{AC_{\max}}$ denote the minimum and maximum duration for which AC can be turned ON/OFF for the considered duration. Based on the model, we select T_p to be 15 min as a change in control input gets reflected after 8–12 min of air-conditioner operation. The problem of maintaining IAQ, reducing energy consumption and maintaining user thermal comfort can be modeled as a multi-objective model predictive controller given by

$$J = \min_{u_{AC}, u_{FA}} \sum_{k=k+1}^{k+N_p} J_{IAQ}(k) + J_{Power}(k) \tag{9}$$

s. t.

Building thermal dynamics: $T(k+1) = aT(k) - bu_{AC}(k) + cw(k) + v(k)$,

Thermal comfort constraints: $T_{min} \leq T(k) \leq T_{max}$,

Control input limits: $u_{AC_{min}} \leq u_{AC}(k) \leq u_{AC_{max}}$,

Fresh air limits: $u_{FA_{min}} \leq u_{AC}(k) \leq u_{FA_{max}}$,

TVOC limits: $0 \leq TVOC(k) \leq \epsilon_{VOC}$,

CO_2 limits: $\epsilon_{CO_2}^{min} \leq CO_2(k) \leq \epsilon_{CO_2}^{max}$,

PM limits: $0 \leq PM(k) \leq \epsilon_{PM}$.

where ϵ_{TVOC},ϵ_{CO_2}, and ϵ_{PM} are the bounds on the IAQ and could be computed as per the ASHRAE standard. The problem in (9) has the following challenges.

(C1) The function J_{IAQ} and the variables (TVOC, CO_2, PM) are difficult to model with dynamical equations as they are highly time-varying with respect to the fresh air induction, temperature, humidity, and other factors influencing the thermal dynamics and IAQ in the room.
(C2) The problem in (9) is a multi-time step, multi-objective optimization problem and solving it in IoT devices is a challenging task.
(C3) Implementing the MPC requires both measurements on IAQ variables as well as forecasts. Obtaining such forecasts is complex task.
(C4) The proposed controller should coordinate the action of the fresh air damper and energy optimizer for the air-conditioner which is difficult due to absence of equations describing their interconnections.
(C5) Sensor and the IoT architecture for implementing the controller above should be implemented.

In what follows, we address the challenges above and modify the existing VRV system into an effective ventilation scheme.

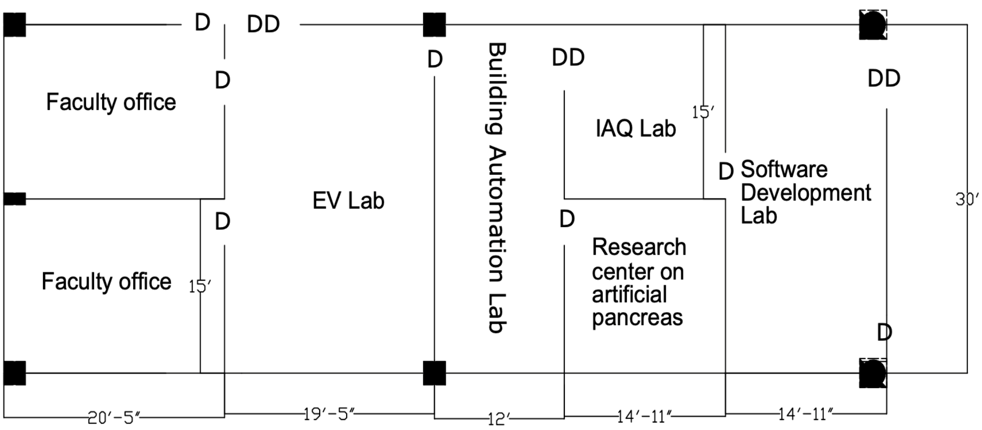

Figure 1. C-RACE laboratory layout located at Kalasalingam University, India (D–Door, DD–Double Door).

3. Novel Hybrid Ventilation System and Soft-Sensor

To implement the MPC with multiple objectives, we first decompose the problem into two parts: (i) Energy optimizer and (ii) IAQ optimizer. Both the optimizers are coupled through the fresh air induction, which influences the thermal dynamics of the zone thereby the energy consumption. Our idea of energy optimizer is to design a device that switches between air-conditioner and fan to maintain thermal comfort but reduce energy consumption using a predictive controller. To this extent, we first require sensor measurements on temperature, humidity and occupancy (to detect cooling loads). Then, the next step is to design the energy optimizer based on the fresh air flow which will be discussed later.

3.1. Sensor Module: Energy Optimizer

The sensor module for the energy optimizer is shown in Figure 2. It consists of a temperature and humidity sensor which we use a DHT11 sensor which can measure both temperature and humidity. To measure occupancy, we use carbon dioxide sensor and passive infra-red (PIR) sensor. The carbon dioxide sensor has delays to measure the occupancy and PIR sensor have errors in counting. To overcome this, we build a soft-sensor on top of the sensor to validate the CO_2 levels (see Section 3.3).

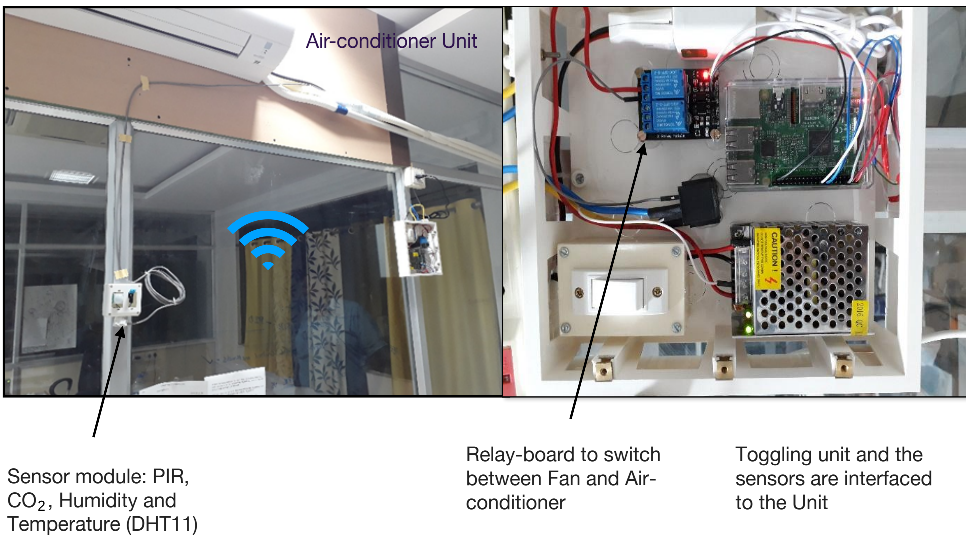

Figure 2. The sensor and controller units used for energy savings.

The PIR motion sensor, carbon dioxide sensor, temperature, and humidity sensor are interfaced to RPi. The RPi is connected to the Ethernet and it acts as a gateway to transmit the sensed information to the server. We use the Message Queuing Telemetry Transport protocol at the application layer to transmit the sensed information. The server uses SQL routines to store the information in the database.

3.2. Energy and IAQ Optimizer

The second step is to implement the control that saves energy, maintains thermal comfort and guarantees IAQ. However, as mentioned earlier these are competing objectives and also there are challenges (C1)–(C5) that needs to be addressed. To address challenges (C1) and (C2), we first decouple the problem of maintaining IAQ and energy optimization plus thermal comfort by designing a hybrid ventilation system. Next, we solve the problems independently but exploit the power of IoT to couple them. In what follows, we describe the different elements used in our implementation.

The hybrid ventilation system consists of two parts: energy optimizer and IAQ optimizer. To decouple the multiple objectives but coordinate the actions, we select the fresh air infusion flow rate as the variable coupling the energy and IAQ optimizers. One can observe that the problem of fresh air induction is quite challenging as the function to approximate IAQ is time-varying and depends on too many parameters. To overcome this, instead of designing a fresh air damper, we use a demand controlled ventilation system for maintaining the IAQ. In this paper, we select the RENSONs' Healthbox3.0 based on analysis performed with various scheme. The Healthbox3.0 is a DCV that controls fresh air induction based on TVOC. (measured in ppb), CO_2 (measured in ppm), humidity, and temperature. The installation of the RENSON Healthbox 3.0 in the C-RACE lab is shown in Figure 3. Consequently, the DCV will introduce fresh air depending on the IAQ in the particular room. Still particulate matter is not considered and we install PM2.5 sensor additionally to measure this variable. The Healthbox 3.0 is installed in the IAQ lab of C-RACE and it samples air from the different labs to change the fresh air induction. The system has inbuilt sensors to measure the IAQ variables which could be transmitted to database through simple SQL scripts by writing the variables into an excel or CSV files.

Figure 3. RENSON Healthbox 3.0 DCV Installation.

The next step is to connect the DCV to the IoT and other interfaces. However, the sensors need to be calibrated. To this extent, we first install the mobileApp provided by RENSON and then the calibration is performed. The flow information about the fresh air is then passed on to the Gateway (RPi) which uses this information to optimize the energy and also for the soft-sensor to compute carbon dioxide. The hybrid ventilation scheme is shown in Figure 4.

As the IAQ objective is now decoupled with the DCV, the energy optimizer solves the following optimization problem to implement the MPC.

$$J = \min_{u_{AC}} \sum_{k=k+1}^{k+N_p} P_{AC} u_{AC} \tag{10}$$

s. t.

$$\begin{aligned}
&\text{Building thermal dynamics: } T(k+1) = aT(k) - bu_{AC}(k) + cw(k) + v(k) \\
&\text{Thermal comfort constraints: } T_{min} \leq T(k) \leq T_{max} \\
&\text{Control input limits: } u_{AC_{min}} \leq u_{AC}(k) \leq u_{AC_{max}} \qquad \forall k \in \{k+1, \ldots, k+N_p\}
\end{aligned}$$

The problem in Equation (10) is a linear programming problem and we used Gnu Linear Programming Kit (GLPK) to implement the controller in RPi. The implemented controller obtained weather forecasts using webservices in Python, and the cooling load estimates were obtained based on the CO_2 predictions from soft-sensor. To address challenge (C4), i.e., absence of coupling between energy and IAQ optimization, we use the flow information and this coupling is solved inherently. Moreover, the hybrid ventilation system also implemented the IoT architecture for realizing the controller addressing the challenge (C5). The only problem to be tackled now is the development of soft-sensor for IAQ which is presented in the rest of the section.

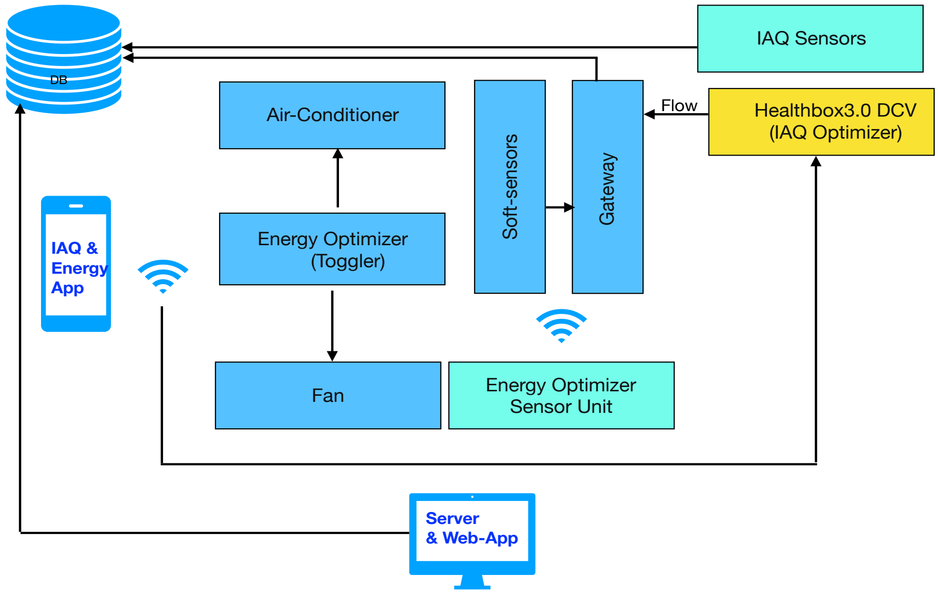

Figure 4. Schematic of the novel hybrid ventilation system.

3.3. *Soft-Sensor for IAQ and Cooling Loads*

As stated earlier, IAQ and cooling load due to fresh air induction due to DCV is a challenging problem due to complex dynamics of these variables. Finding dynamical equations for modeling it is a challenging task. Therefore, it makes perfect sense to develop models using databased methods to estimate the IAQ and cooling load. In this context, time-series data of IAQ variables is available from the hybrid ventilation system designed by us. Therefore, data required for building soft-sensors required for our application is available to us as shown in Figure 5. These are IAQ sensor readings (temperature, RH, CO_2 and TVOC) collected from the Helathbox 3.0 for 10 days with a sampling interval of 15 min. To study the dependence of the parameters, we studied the correlation among the parameters (see, Table 1). One can see that there is no strong correlation between the parameters. Therefore, the univariate forecasting model is used to simplify our analysis. Similarly, the cooling load should be estimated from coupling variable fresh air flow in individual zones. However, cooling loads are also affected by occupancy, stray heating loads such as lighting, computers etc. Therefore, building soft-sensors for cooling loads using data-based methods requires rethinking. In this paper, we use the zone thermal dynamics to estimate the cooling load as a function of fresh air flow and heat generated in the zone as will be illustrated in this section.

Table 1. Correlation matrix of indoor air quality (IAQ) parameters.

	TVOC	**RH**	**CO_2**	**Temp**
TVOC	1	−0.07	0.03	−0.05
RH	−0.07	1	−0.45	0.05
CO_2	0.03	−0.45	1	0.3
temp	−0.05	0.05	0.3	1

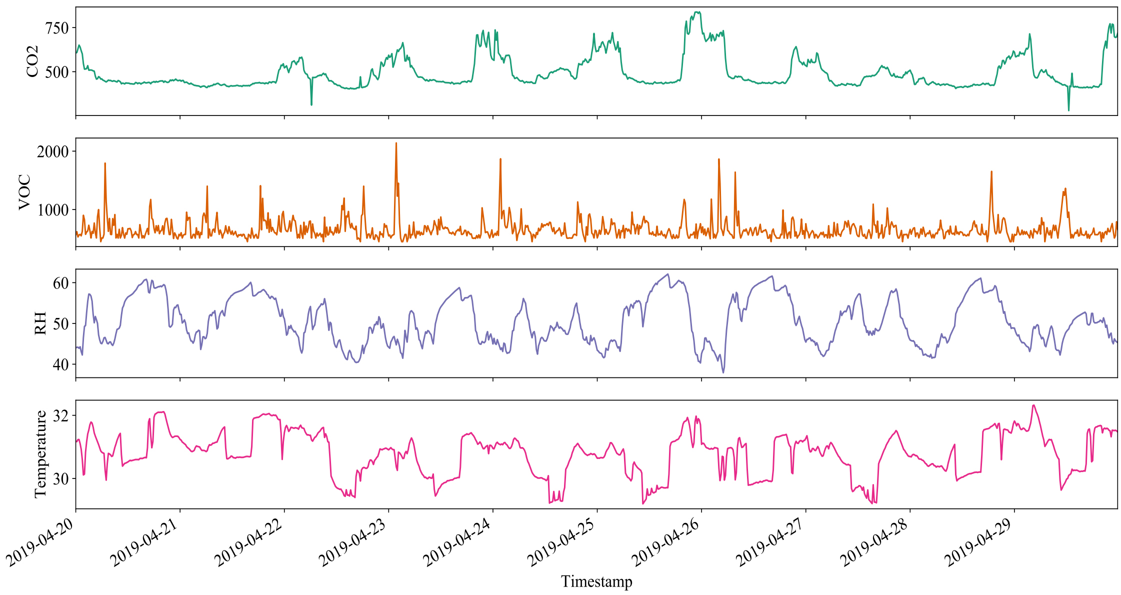

Figure 5. IAQ measurements for 10 days with 15 min interval.

3.3.1. Soft-Sensors for Cooling Load Measurement

The cooling load is also due to fresh air induction and the effect of cooling load is measured from the prediction equation using the zone thermal dynamic model as

$$Q(k) = T(k+1) - aT(k) + bu_{AC}(k) + cw(k) \tag{11}$$

The above equation gives an estimate of the cooling load as well as the effect of fresh air induction. The fresh air induction and the raise in temperature due to weather, current room temperature, and control input, i.e., the time for which the air-conditioner is kept ON/OFF is used to train the cooling load estimator. We use a simple radial basis function neural networks (RBFNN) to estimate the cooling load.

3.3.2. Soft-Sensors for IAQ

As our idea is to design a soft-sensor for IAQ with univariate analysis, we consider the use of deep neural networks as they tend to outperform other models used in computer vision. In recent years, deep neural networks have been shown to outperform previous state-of-the-art machine learning approaches in various application domains [25]. Convolutional Neural Networks (CNN) is a special type of deep neural networks which is mainly used to handle 2D input data such as images. A CNN architecture is built by stacking three main types of layers: *convolutional*, *pooling*, and *fully-connected*. The convolutional layer maps the input data to a feature map by performing the convolution operation (dot product between the input and a filter) by sliding over the input data. The output of convolution operation is passed through an activation function that controls neuron activation. Rectified Linear Unit (ReLU) is a commonly used activation function to introduce non-linearity into the neuron's output. The pooling layers are often included between the successive convolutional layers. They are useful in reducing the dimensionality of feature maps to avoid overfitting. Max pooling is commonly kept as it is the most dominant spatial relationship. Next, the pooling layer output is flattened and given as input to the fully connected dense layer that computes the final model output.

Our CNN model architecture for short-term forecasting is shown in Figure 6. It takes the past IAQ sensor readings as input and performs a one-step prediction. In our experiments, the past 24 sensor readings (6 h long) are used as input. Next, we added two 1-dimensional convolutional layers (kernel size 2) with ReLU activation function that learns the trend and seasonality in the sensor data.

This is followed by a 1-dimensional max pooling layer (pool size 2) that reduces the feature map dimension into half. Consequently, the pooling layer output is fed to the fully connected layer that yields the final prediction. We implemented our CNN architecture in Python 3 using the keras library (https://keras.io/). An early stopping method was also used to optimize the training process.

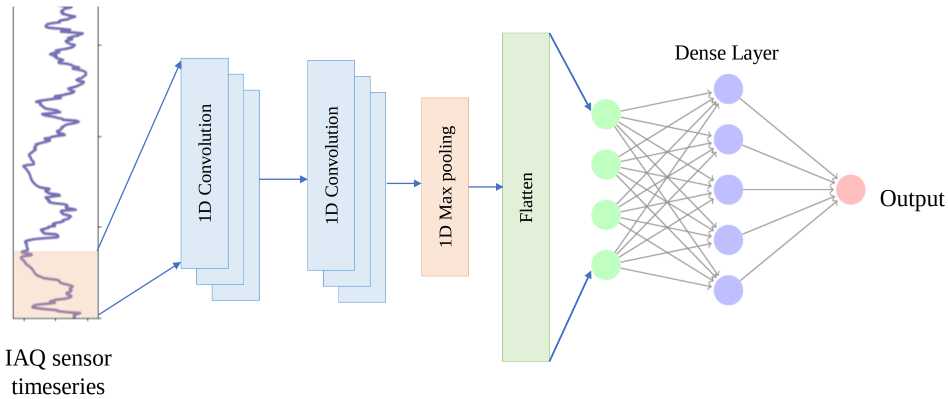

Figure 6. The convolutional neural network (CNN) model architecture for forecasting IAQ sensor data.

3.4. Calibration of IAQ Sensors Using MobileApp

To calibrate the sensors, a mobileApp provided by Renson was used. It is an Android application for Renson Healthbox 3.0 that allows the user to access and calibrate the device. Calibration is done by establishing connection between the device and mobile. The calibration tool performs auto-configuration and calibration is done for the actuators and sensors using the mobileApp automatically. Once installed, the Renson Healthbox 3.0 could connect to cloud and other platforms to port the data. There is also a portal provided by the Healthbox 3.0 for porting the data. The calibration is for control valves that open the vanes for supplying fresh air and takes up to 3–6 min. This will adjust the nominal air-flow rate to individual zones as well. The calibration procedure with the mobileApp is shown in Figure 7.

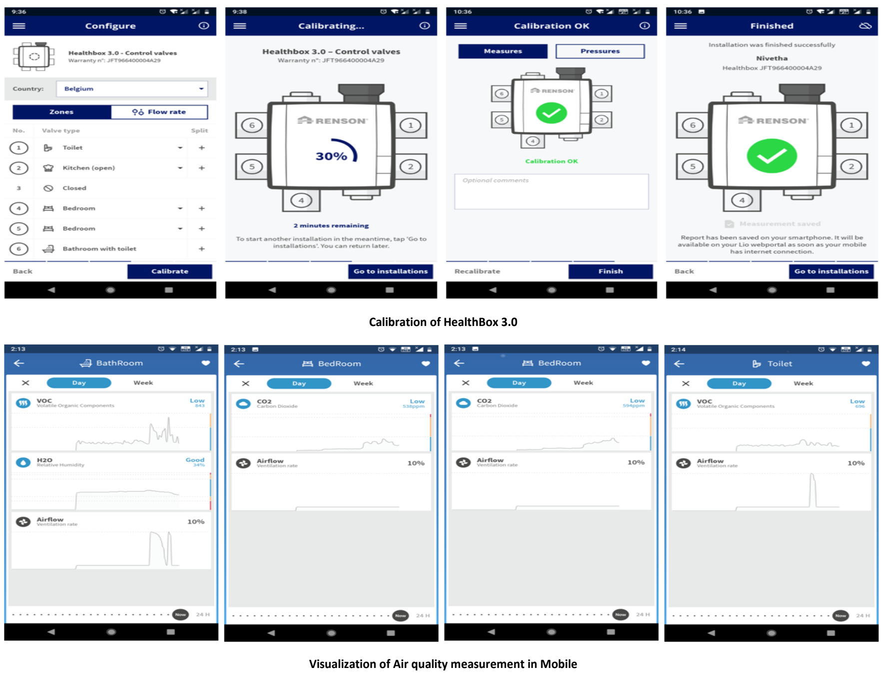

Figure 7. Calibration with MobileApp for Renson Healthbox 3.0.

4. Results

4.1. Soft-Sensors for IAQ

The soft sensor effectiveness was validated using the data collected from the hybrid ventilation system in Figure 4. We used 80% of our dataset to training our CNN models and the remaining 20% for testing. The descriptive statistics of the collected data is shown in Table 2. We summarize the performance of our short term forecasting model for each IAQ sensor using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) in Table 3 and visualization in Figure 8. The forecasting error of TVOC is high compared to other sensors due to no seasonality in the raw data. This requires further investigation, possibly extending our CNN model with Long Short-Term Memory [26]. The forecasting error of all other sensors is less than 5%.

Table 2. Descriptive statistics of the collected IAQ sensor data.

Statistics	CO_2	TVOC	RH	Temperature
Mean	492.90	656.81	50.70	30.79
Std	89.23	172.37	5.62	0.68
Min	279.67	450.00	37.90	29.20
25%	433.33	567.89	45.93	30.27
50%	453.83	611.24	49.89	30.89
75%	525.92	700.16	55.76	31.28
Max	839.00	2,140.36	62.11	32.32

Table 3. Comparison of short-term forecasting results using mean absolute percentage error (MAPE) and mean absolute error (MAE).

Error Metrics	CO_2	TVOC	RH	Temperature
MAPE (%)	4.1	13.5	1.9	0.6
MAE	19.1	96.9	1.0	0.2

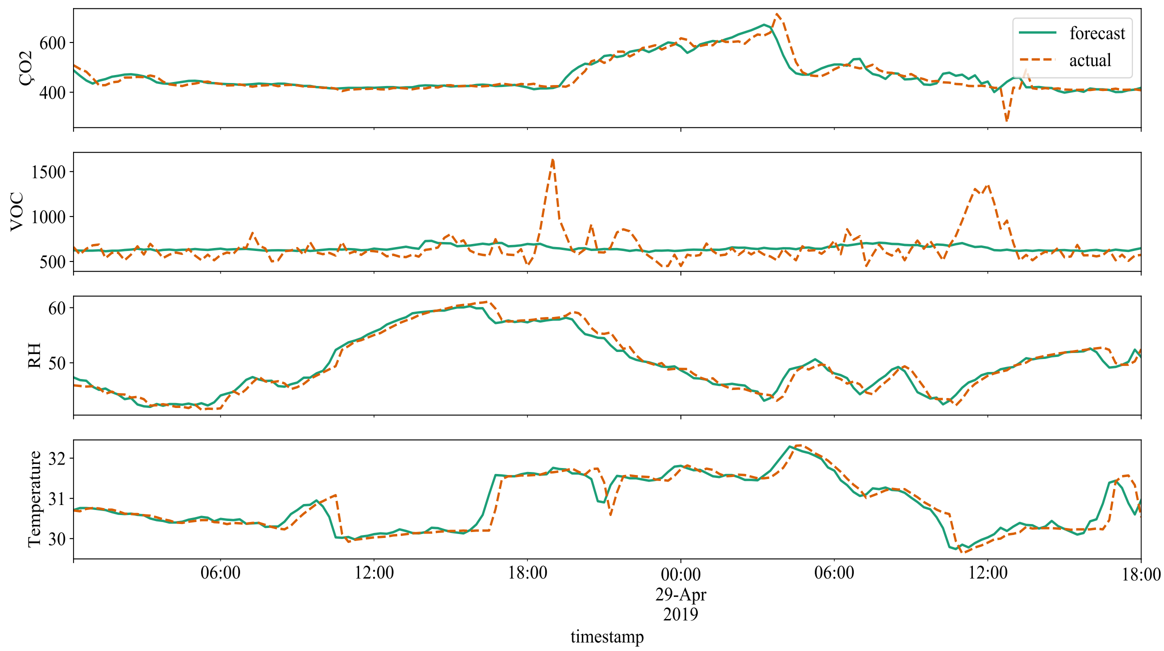

Figure 8. Visualization of IAQ sensor forecasting using CNN model.

As an example, consider the scenario wherein the objective is to maintain both IAQ and minimize power consumption. Suppose, if the IAQ is bad, then the Healthbox 3.0 which is a DCV introduces more fresh air which increases the cooling load. However, the DCV controls the IAQ parameters efficiently. On the other hand, the increase in cooling load is forecasted as increase in cooling loads and fed to the toggler which is a model based controller. It fuses this information into the model and predicts future temperature evolution in a particular zone and then tries to optimize the energy supplied to the individual zones based on temperature set-points provided by the user by adjusting the duty cycle of the toggler. This way both IAQ and energy is optimized by the hybrid ventilation scheme.

4.2. Indoor Air Quality

The performance of the DCV with the proposed energy optimizer is evaluated. For this study, we first collect information on the ventilated space over different periods. Then, we compare the results with and without hybrid ventilation system. It was seen that without the hybrid ventilation system the TVOC, carbon dioxide, temperature, and humidity levels were not maintained, as there was no control on IAQ and space cooling.

The variations in humidity with the hybrid ventilation scheme and the energy optimizer is shown in Figure 9. One can see that the humidity is maintained within acceptable values of 60 even during the nights when the ventilation system is shut out. This is due to the pre-conditioning created by the fresh air introduced by the proposed hybrid ventilation system. Contrary to this before installing the Healthbox 3.0, the humidity cannot be maintained and the behavior is almost random.

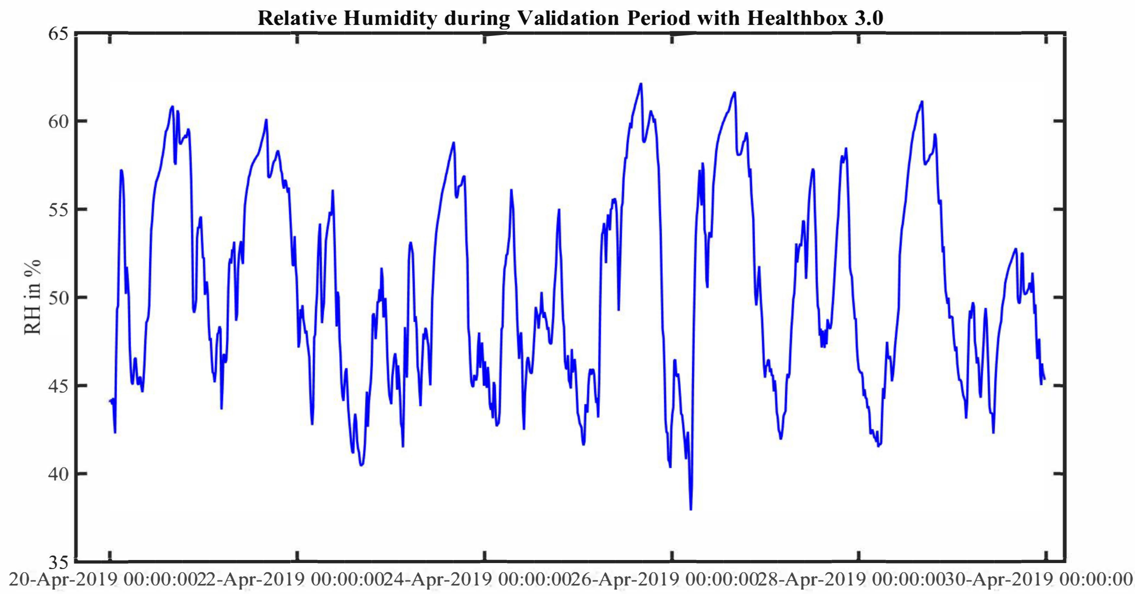

Figure 9. Humidity variations with the hybrid ventilation system.

The variation in CO_2 levels with the hybrid ventilation system installed is shown in Figure 10. The CO_2 levels are well maintained with the proposed energy and IAQ optimizer. A clear pattern of the variation is shown and the maximum value reaches 850 ppm though there are approximately 5–6 occupants in the room. This results shows the capability of the proposed system to maintain CO_2 levels. While the Helathbox maintains the IAQ, the energy optimizer also coordinates its action by using the fresh-air flow as the variable.

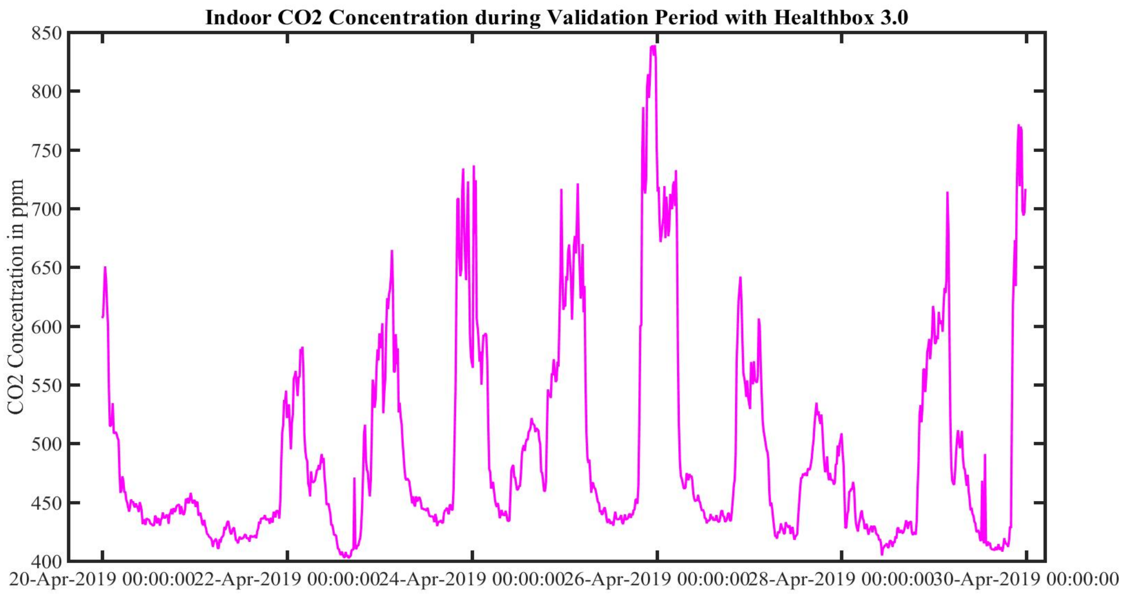

Figure 10. The carbon dioxide levels with Hybrid Ventilation system.

The variations in TVOC with the proposed hybrid ventilation system is shown in Figure 11. One can see that the TVOC is maintained within a ppb of 1000 during normal days and exceeds to 1400 only when the system is turned OFF. This results shows the ability of the system to maintain IAQ by limiting the TVOC.

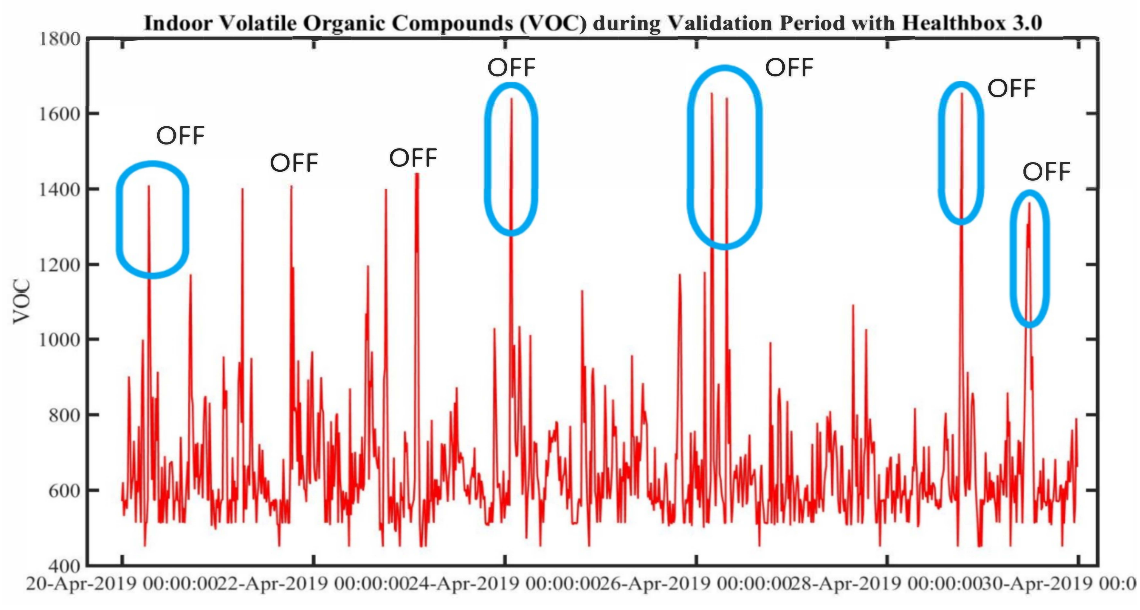

Figure 11. The Total Volatile Organic Compound levels with Hybrid Ventilation system.

4.3. IAQ and Thermal Comfort

As seen in the results, one can see that the IAQ variables are maintained within acceptable values throughout the period, and the temperature is also maintained within user-defined comfort values by the system. The occasional spurts represent the night times when the system is kept off, but the temperature is maintained well within the user defined comfort margin of 20–25 degree °Celsius.

4.4. Energy Optimizer

The performance of the energy optimizer for a 12 h period with a sampling time of 15 min is shown in Figure 12. Here, the control input is the duty cycle, i.e., $u_{AC} = \frac{t_{ON}}{T_p}$. A value of $u_{AC} = 0.5$ means that the air-conditioner should be operated for 7.5 min within 15 min. However, this gives rise to frequent switching and transient energy gets wasted. Therefore, to overcome this, we use an averaging approach, i.e., the control inputs computed at two time-instants are implemented for a time-frame of 30 min. For example, $u_{AC}(k) = 0.5$ and $u_{AC}(k-1) = 0.3$, where $k-1$ was not implemented to avoid transient energy loss, then a total of 12.5 min is turned ON during the kth time-instant. Such an averaging may sometimes result in the zone temperature to raise above the comfort band of 28 °C. However, considering that the time constant of the zone is very high in the order of 12–13 min, this is negligible period for which the thermal comfort could be breached by a small margin, but the savings in transient energy is quite high. Therefore, we implement the wait and apply strategy to reduce the transient energy consumption.

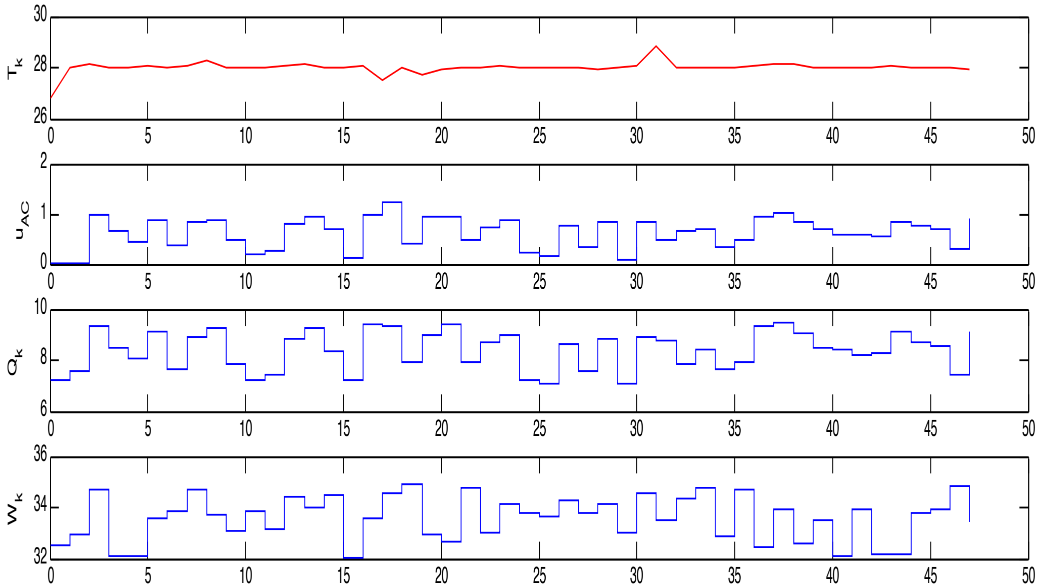

Figure 12. Variations in zone temperature, control input, heating due to cooling load, and ambient temperature (x-axis: 1 unit = 15 min).

The energy consumption was recorded with and without the proposed control strategy. We found that an average saving of 19.2–21.4% was observed with the proposed control strategy over conventional thermostat control while maintaining the IAQ. These savings are for 12 h period in a working day. The savings are mainly due to switching between fan and air conditioner. This result illustrates the energy savings potential of the proposed hybrid ventilation and control scheme.

Our results showed that the proposed hybrid ventilation scheme achieved good IAQ and energy savings without breaching the comfort band proposed by the occupant. We also showed that an energy savings of up to 19–21% can be achieved, and the IAQ parameters were maintained within bounds specified. We also demonstrated the role of soft-sensors and implementation aspect of the proposed hybrid ventilation scheme, i.e., demand controlled ventilation, sensors for measuring IAQ parameters and energy relevant data, communication architecture and other aspects were also presented. The results demonstrated the value of soft-sensor to measure parameters like cooling loads, TVOC, carbon dioxide concentration and others which were not possible before. An additional benefit of soft-sensor is the ability to generate short-term predictions which could be used to plan ventilation schedules.

5. Conclusions

This paper presented a novel design of a hybrid ventilation system for optimizing energy consumption in variable air volume (VRV) systems while maintaining indoor air quality (IAQ) and the thermal comfort of the building occupants. We showed that the problem is multi-objective, multi-time step optimization problem as the objective to optimize both IAQ and energy requires a model predictive controller (MPC). As such implementing MPC schemes on low-cost hardware is a challenge and the absence of sensed information/predictions on IAQ and cooling loads posed additional challenges. To overcome this, we proposed IoT based sensing that was extended with deep learning tools to design soft-sensors that provided measurements on parameters, which could not be measured with physical sensors. Then, the multiple objectives was decoupled into IAQ and energy savings. To achieve IAQ we proposed a novel hybrid ventilation system which used RENSONs' Healthbox 3.0, which is an off-the-shelf demand controlled ventilation. On the other hand, we designed an MPC in Rasperry Pi using the Gnu Linear Programming Kit (GLPK) which provided optimal solution to the multi-time step optimization problem to realize the energy optimizer. We provided results which showed the performance of soft-sensors, IAQ and energy optimization capabilities of the hybrid ventilation scheme while meeting user defined comfort bands. Extending the hybrid ventilation scheme to other IAQ measures and including thermal comfort with predictive mean vote or other standards is the future course of this investigation.

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Abbreviations

The following abbreviations are used in this manuscript.

HVAC	Heating, Ventilation and Air-Conditioning
VRV	Variable Refrigerant Volume
IoT	Internet of Things
IAQ	Indoor Air Quality
TVOC	Total Volatile Organic Compound
PM	Particulate Matter
MPC	Model Predictive Control
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
DCV	Demand Controlled Ventilation
CNN	Convolution Neural Network
EPA	Environmental Protection Agency
C-RACE	Center for Research in Automatic Control Engineering

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